Transferability of a random forest model for resistance prediction between different regions in Europe

Übertragbarkeit von „Random Forest" Vorhersagemodellen für die Entwicklung von Resistenzen zwischen unterschiedlichen Regionen in Europa

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Abstract

Herbicides are an important technology in the Integrated Weed Management (IWM) tool box aiming to control weeds in modern agriculture. Prediction tools to evaluate the risk of resistance evolution will greatly help to choose the best IWM strategy adapted to the local field situation. In a previous work (HERRMANN et al., 2016) a random forest risk assessment model based on a data set comprising field history, management, and resistance status of *Alopecurus myosuroides* populations in Southern Germany was created. In this study transferability of the model with respect to regions and comparable weeds was analysed based on a similar dataset from a region in Northern France. The data from France also contained information on *Lolium* spp. The data related to Germany and France were subjected to a cross-validation procedure by interchanging test and training data. Results showed that acceptable predictions can be obtained for training data from Germany applied to France and vice versa. Resistance status in LOLSS samples from France can be predicted with a good accuracy based on a combined training set of *A. myosuroides* samples from Germany and France.

Keywords: Artificial intelligence, geographical variation, herbicide resistance prediction, resistance management

Zusammenfassung

Herbizide sind eine wichtige Komponente der integrierten Unkrautbekämpfung (IWM) in der modernen Landwirtschaft. Entscheidungshilfesysteme zur Bewertung des Risikos einer Resistenzentwicklung können in hohem Maße dazu beitragen, die beste IWM-Strategie zu wählen, die an die lokale Situation vor Ort angepasst ist. In einer vorherigen Studie (HERRMANN et al., 2016) wurde ein „Random Forest" Vorhersagemodell zur Bewertung des Risikos für das Auftreten von Resistenzen in *Alopecurus myosuroides* (ALOMY) Populationen in Süddeutschland erstellt, das auf langjährigen Schlaghistorien beruht. In der vorliegenden Studie wurde die Übertragbarkeit des Vorhersagemodells in Bezug auf Regionen und vergleichbare Unkräuter anhand eines ähnlichen Datensatzes aus einer Region in Nordfrankreich analysiert. Die französischen Daten enthalten auch Informationen zu *Lolium* spp. (LOLSS, hauptsächlich *Lolium perenne*). Die deutschen und französischen Daten wurden durch Austausch von Test- und Trainingsdaten einem Kreuzvalidierungsverfahren unterzogen. Die Ergebnisse zeigen, dass von Trainingsdaten aus Deutschland akzeptable Vorhersagen für Frankreich erhalten werden können und umgekehrt. Der Resistenzstatus von Proben von *Lolium* spp. aus Frankreich kann mit einer guten Genauigkeit anhand eines gemeinsamen Trainingssatzes von Proben von *A. myosuroides* aus Deutschland und Frankreich vorhergesagt werden.

Stichwörter: Geografische Variation, Künstliche Intelligenz, Resistenz Management, Vorhersage von Herbizidresistenz

Introduction

In the last decades, herbicide resistance has become a major issue for many weeds (POWLES and YU, 2010; GRESSEL, 2009). Weed population dynamics and control is a complex process depending not only on the choice of appropriate herbicides but also on cropping patterns, cultural techniques and other crop management practices (HAWKINS et al., 2019). In addition, the time scales involved in resistance development comprise several years. Weed population dynamics is not a deterministic process. Variables such as weather conditions, spatial inhomogeneity of the seed bank, initial frequency of resistant biotypes, spray distribution patterns influence the system in a random manner (ZWERGER et al., 2017). Therefore, it is not surprising, that some farmers have resistant weeds in their fields and others not. On the other hand, long term managing practices may differ considerably. It is unknown, if there are recognizable patterns related to field history influencing the development of herbicide resistance and if so, can the driving variables for the emergence of resistant biotypes be identified. To answer these questions a reliable data base of field histories has to be established. In a previous study (HERRMANN, 2016) it was shown that a random forest model could be applied successfully to the prediction of the resistance status of *A. myosuroides* in the Hohenlohe area in southern Germany. The question arises, whether the patterns found in the Hohenlohe data are specific for this region or whether they are transferable not only to other regions (Northern France) but also to other grass weeds (*Lolium* spp.). It is the aim of this study to establish a prediction model based on artificial intelligence (AI), which enables a farmer to assess that an herbicide resistance problem is developing.

Materials and Methods

Data

The data includes the field histories and resistance status of 98 fields from the Hohenlohe area in Germany and 131 from the Champagne area in France. For the Champagne also a Lolium spp. data set for 49 fields was obtained with resistance status and field history information. Predictor variables comprise crop rotation, number of crops, seeding date, soil cultivation and herbicide applications. There are 19 predictors (Tab. 1).

Tab. 1 List of predictor variables.

Tab. 1 *Liste der Prediktorvariablen.*

Variable	Explanation
WCereals	The proportion of winter cereals in the crop rotation
SCereals	The proportion of summer cereals in the crop rotation
WCrops	The proportion of winter crops in the crop rotation
SCrops	The proportion of Summer crops in the crop rotation
NCrops	Number of different crops used (winter wheat, triticale and spelt were counted as one)
DicotCrops	The number of dicot crops in the crop rotation
Corn	The amount of corn in the crop rotation
SeedingDate	The proportion of delayed seeding events in the crop rotation
Ploughing	The proportion of ploughing in the crop rotation
ALOMYHerb	The number of herbicide applications against *A. myosuroides* divided by the number of years observed
Herb_App	Total number of herbicide applications in the crop rotation divided by the number of years observed
Molecules	The number of different active ingredients applied
GrpB_Products	The number of different GrpB-Products applied in the crop rotation
UniqueMoA_Grasses	The number of different Modes of Action used against *A. myosuroides*
ALOMYHerbGrpB	The number of ALS-Inhibitor (HRAC Group B) divided by the number of years observed
GrpG_App	The number of Glyphosate Application in the crop rotation
GrpA_App	The number of ACCase application in the crop rotation
Flufenacet	The proportion of Flufenacet (HRAC K3) used against *A. myosuroides*
DM	diversity of management (ploughing, delayed seeding, herbicides, spring crops)

An additional predictor DM (diversity of management) was devised, which is an index for the diversity of *A. myosuroides* management (HERRMANN, 2016). This variable considers the number of different measures specific for weed control within a year. These comprise delayed seeding, ploughing, summer crops and the use of multiple modes of action. If a measure is applied, the respective score takes the value of 1 otherwise the value of 0. If all measures are applied, the maximum value of DM is 4, if none is applied the score is 0. The index ranges therefore between 0 and 4. E.g. in winter wheat, using two modes of action (score 1) and ploughing (score 1) results in a

DM value of 2, while shallow tillage (score 0) and only one mode of action (score 0) give a DM value of 0. DM values are averaged for the time frame of the 6yrs being considered. Resistance status was established by greenhouse tests with collected seeds and subsequent genetic analysis of the seedlings to determine target site resistance and analytics to determine metabolic resistance when appropriate for the samples from France and Germany. Fields were classified as resistant if target-site resistance or metabolic resistance or both were detected in the samples and/or survivals were observed in the greenhouse (HERRMANN et al., 2016). A descriptive data analysis was performed to ensure that the data sets of both countries have a similar structure. As an example Figure 1 shows the comparison between 4 selected variables, which have a possible impact on resistance development. The figure reveals slightly different management practices concerning late seedings and summer crops. In France herbicides which are specific for *A. myosuroides* are applied more frequently than in Germany. In both regions ploughless soil tillage is common. The correlation structures of the predictor variables as shown in Figure 2 are similar for both data sets of A. myosuroides. Note the high correlations of herbicide application with *A. myosuroides* herbicides or between winter and summer crops. Climatic conditions are slightly different in the two regions; mean temperature and precipitation are higher in the Champagne than in the Hohenlohe region

AI Method

For our classification problem with 20 predictor variables, partly correlated samples, and small sample sizes, the random forest method (BREIMAN, 2001) is most convenient, since it can cope with

i) "small n large p" problems, i.e. large features small sample size with high accuracy
ii) complex interactions
iii) and even highly correlated predictor variables (STROBL et al., 2008).

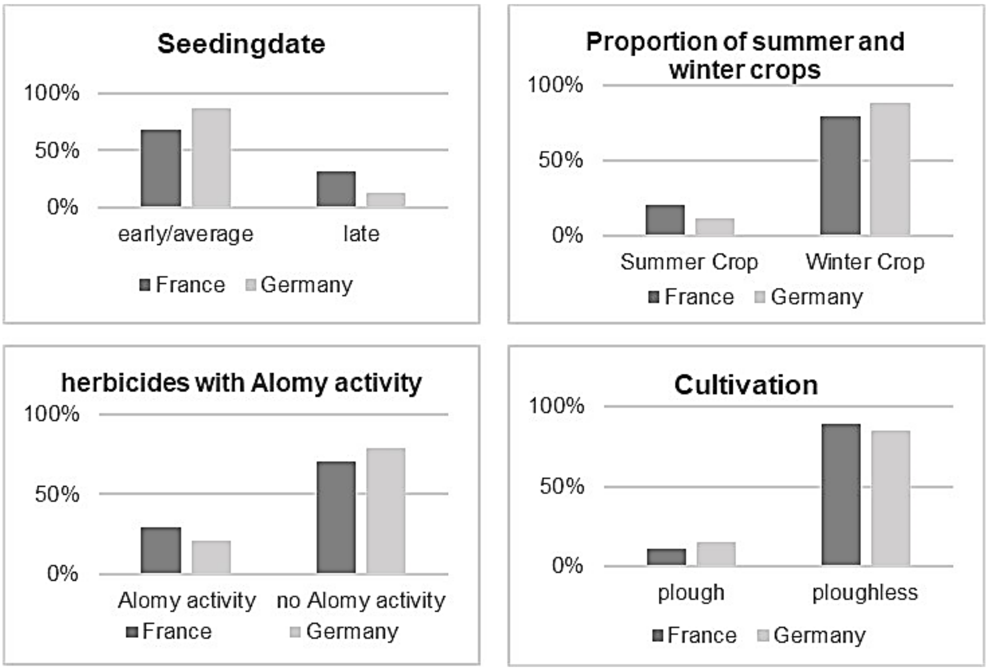

Fig. 1 Comparison of selected variables between Germany and France (seeding date, summer/winter crops, *Alopecurus myosuroides* specific herbicides, cultivation).

***Abb. 1** Ausgewählte Variablen im Vergleich von Deutschland und Frankreich (Saatzeitpunkt, Sommer-/Winterkultur, spezifische Herbizide für Alopecurus myosuroides, Pflugeinsatz).*

The method is shortly described as follows: An ensemble of uncorrelated decision trees, a "Random forest", is generated by a training data set. For the classification of a new case, each of the trees classifies the case individually i.e. the tree "votes" for that case. The final classification is the one with the most "votes". Sometimes, only a few of the predictor variables have a significant impact on the response. Therefore, it is of interest to analyse the importance of the predictors. Usual importance measures are the Gini index and the mean decrease accuracy index (HASTIE et al., 2017). In all analyses, the data were split into training data (75%) and test data (25%).

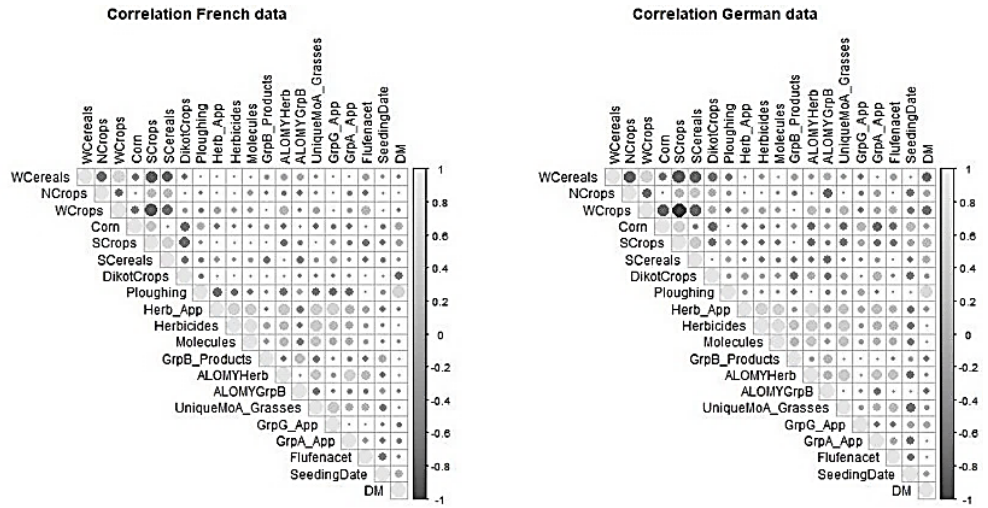

Fig. 2 Correlation structure of the data sets. The strength of the correlation is indicated by the size of the symbols and by the gray scale.

***Abb. 2** Korrelationsstruktur der Datensätze. Die Stärke der Korrelation ist durch die Größe der Symbole und die Grauskala kodiert.*

Procedure of the analysis

The transferability of the random forest model was analysed in three steps.
1. French and German data sets were analysed separately.
2. Training and test data were interchanged, e.g. German data were used to train the random forest and French data wer predicted.
3. French and German data were merged and used as training data set. Test data sets were taken from French and German data, from French data only and for German data only respectively.
Additionally, a French data set for *Lolium* spp. was tested.

Results

Separate analyses of the data sets of both countries (1. step) gave similar results for both the accuracy as well as the type I and type II errors (Fig. 3). In the second step we found that prediction accuracies are more different than in step one, if training and test data between France and Germany are exchanged. However, when merging the data sets as described above (3. step) all combinations yielded similar results comparable to those obtained in step one. Two general features are apparent. In all combinations, type II errors (with the exception of training with French data and testing with German data) are larger than type I errors. These results indicate that in both countries the same patterns of management are likely to develop resistance. The most striking feature of the Gini index is the high rank of DM, which measures the diversity of management (Fig. 4). Large differences in ranking occur for the variable Scereals (proportion of summer cereals in the crop rotation). However, for all data sets, 4 variables out of the first six places are identical. These are the number of ALS-Inhibitor applications (ALOMYGrpB), DM, the number of different group B products used (GrpB_Products), and the number of different active ingredients which were applied (Molecules). The mean decrease of accuracy measure gives similar results (graph not shown here): the variables ALOMYGrpB and GrB_Products and variables pertaining to crop rotation are highly ranked.

Employing the French data set and the merged dataset from France and Germany respectively, a random forest model was applied to *Lolium* spp. data from France. Note that this data set comprises only resistant cases so the results have to be interpreted with caution. With the combined German-French data set only one case was misclassified as sensitive (Fig. 5).

For *A. myosuroides* the results show that in most combinations type I errors are lower than type II errors, i.e. false positive classifications are more frequent. There are two possible explanations:

i) The misclassified sensitive field has features similar to the features of resistant fields, but resistance has not developed as yet or has not been found in the plant samples.

ii) There are other factors not considered e.g. soil properties and weather patterns.

The results clearly show that the main factors promoting the development of *A. myosuroides* resistance are frequent use of herbicides of HRAC Group B (ALS inhibitors), and low diversity of management. The importance of these factors is seen in all combinations of the data sets. For the German data, the factor ploughing turned out to be most important. Here, we see a possible conflict between soil conservation and avoidance of resistance. In the analysis based on the French data and also on the combined data ploughing has only a minor importance. For the French data, the variable ALOMYgrB (ALS inhibitors) is most important.

1. step

training: german data
test: german data

		Reference	
		S	R
Prediction	S	2	2
	R	4	16

Accuracy: 75%
Type I error: 0.66
Type II error: 0.11

training: french data
test: french data

		Reference	
		S	R
Prediction	S	1	2
	R	5	24

Accuracy: 78%
Type I error: 0.83
Type II error: 0.08

2. step

training: german data
test: french data

		Reference	
		S	R
Prediction	S	7	30
	R	19	75

Accuracy: 63%
Type I error: 0.73
Type II error: 0.29

training: french data
test: german data

		Reference	
		S	R
Prediction	S	0	0
	R	25	73

Accuracy: 75%
Type I error: 1
Type II error: 0

3. step

training: german + french data
test: german + french data

		Reference	
		S	R
Prediction	S	2	5
	R	10	29

Accuracy: 67%
Type I error: 0.83
Type II error: 0.15

training: train german + train french data
test: test french data

		Reference	
		S	R
Prediction	S	2	5
	R	4	21

Accuracy: 72%
Type I error: 0.66
Type II error: 0.19

training: train german + train french data
test: test german data

		Reference	
		S	R
Prediction	S	2	1
	R	4	17

Accuracy: 78%
Type I error: 0.66
Type II error: 0.05

Fig. 3 Performance of the random forest model under different combinations of training and test data. S: sensitive, R: resistant.

Abb. 3 *Zusammenfassende Leistungsergebnisse der Random Forrest Modelle in verschiedenen Kombinationen von Trainings- und Testdatensätzen. S: sensitiv, R: resistent.*

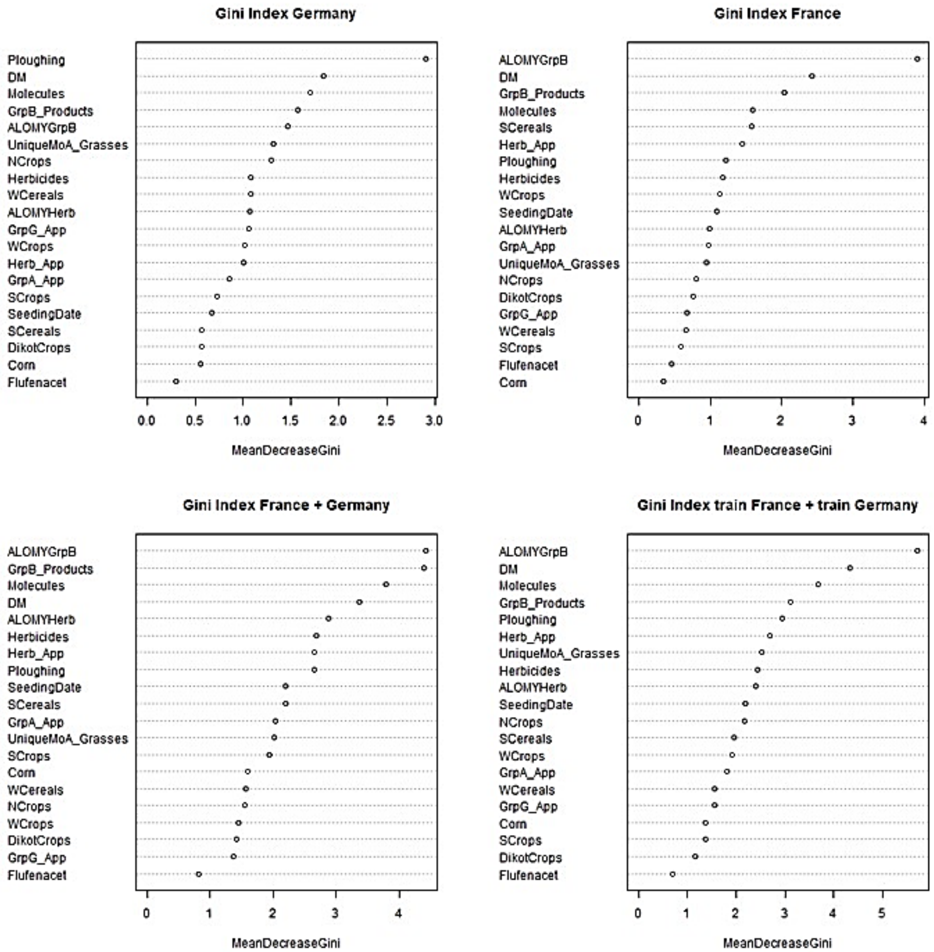

Fig. 4 Comparison of the Gini importance measure for the four training data sets used. Note that 4 variables out of the first six places are identical: ALOMYGrpB, DM, Molecules, GrpB_Products.

Abb. 4 *Vergleich des Gini index/Gewichtungsmaß für die vier Trainingsdatensätze. Zu beachten ist, dass 4 der 6 variablen mit den höchsten Werten identisch sind: ALOMYGrpB, DM, Molecules, GrpB_Products.*

training: french data
test: Lolium data

		Reference	
Prediction		S	R
	S	0	2
	R	0	47

Accuracy: 96%
Type II error: 0.04

training: german + french data
test: Lolium data

		Reference	
Prediction		S	R
	S	0	1
	R	0	48

Accuracy: 98%
Type II error: 0.02

Fig. 5 *Performance of the random forest model trained by the French data set and by the combined French German dataset applied to the grass weed* Lolium *spp., S: sensitive, R: resistant.*

Abb. 5 *Zusammenfassende Leistungsergebnisse der Random Forest Modelle für Lolium spp.. Einmal nur mittels des französischen Datensatzes trainiert, einmal mit dem deutschen und dem französischen gemeinsam, S: sensitiv, R: resistent.*

In conclusion, our study corroborates the recommendations issued by many authors: to prevent resistance development it is important to utilize an overall integrated pest management approach by combining as many management practices comprising the use of different herbicides, diversity in crop rotations and cultivation as possible including cover crops, false seed bed, delayed sowing date, seed destruction, and other non-agronomic practices when appropriate (i.e. BECKIE, 2006; NORSWORTHY et al., 2012; BYRNE et al., 2018).

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